Coding and ANN - assisted Pseudo - Noise Sequence Generator for DS / FH Spread Spectrum Modulation for Wireless Channels

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***Abstract*—One of the challenging issues in Spread-Spectrum Modulation (SSM) is the design of the Pseudo - Random or Pseudo - Noise (PN) sequence generator as an option to the already available methods. This work is related to the use of Artificial Neural Network (ANN) for generation of the PN sequence during transmission and reception of a SSM based system. The benefit of the ANN - assisted PN generator shall be that it will simplify the design process of the PN - generator and yet provide high reliability against disruptions due to intentional disruptions and degradation of signal quality resulting out of variations in channel condition. The performance of the SSM system can be further enhanced by the use of coding. Hamming and cyclic redundancy check (CRC) codes have been used here with the data stream to explore if performance of the SSM system is improved further.**

***Index Terms*—SSM, PN sequence, ANN, Rayleigh, Rician**

I. Introduction

Spread Spectrum Modulation (SSM) is a transmission technique in which a Pseudo-Noise (PN) code independent of the information data is used as a modulation waveform to spread the signal energy over a bandwidth much greater than the signal information bandwidth. This technique decreases the potential interference to other receivers while achieving privacy [1]. For the SSM system performance, the processing gain of the spreading code is one of the major concerns. The processing gain depends on the code length of the spreading code. The larger the processing gain, the better is the system performance [2]. This is dependent on the PN sequence to be used for the SSM. There are several approaches to how a PN sequence can be generated, but this work considers a PN sequence generator assisted by Artificial Neural Network (ANN) for transmission and reception. A direct sequence (DS) spread spectrum signal is generated by the direct mixing of the incoming data with a spreading waveform before the final carrier modulation. But in frequency hopping (FH) the spectrum of a data-modulated carrier is widened by changing the carrier frequency in a pseudo-random manner over a sequence of frequencies called the frequency hopping pattern [3][4][5][6]. A generic SSM setup with both DS and FH approaches is depicted in the Figs. 1 and 2.

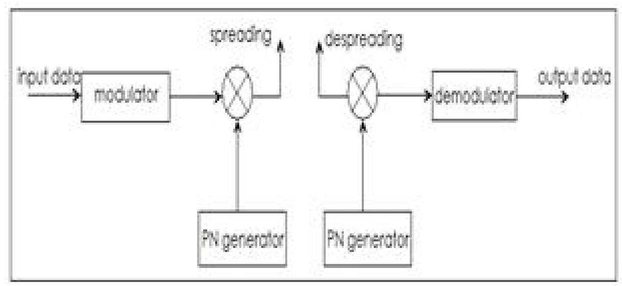

Figure 1 : Direct sequence spread spectrum system

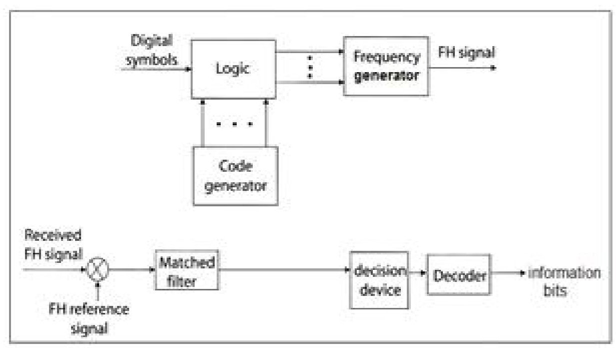

Figure 2 : FHSS transmitter and receiver

II. SYSTEM MODEL

The system model is depicted in Fig. 3. It is constituted by a SSM transmitter with a PN sequence generator formed by an ANN. The receiver is also assisted by an ANN. The ANN is trained to generate the unique PN sequences which are used for transmission and reception of specific data blocks. The core of the system is the ANN. The most important difference with respect to classical information processing techniques is that ANNs are not mathematically programmed, but are trained with examples [7]. The system model related to this work is depicted in Fig. 3 and has the components as described below.

A. ANN Formation

A feed-forward ANN is created with parameters as in Table I. It is known as Multi-Layer Perceptron (MLP) (Fig. 4). The equation for output in a MLP with one hidden layer is given as [8]:

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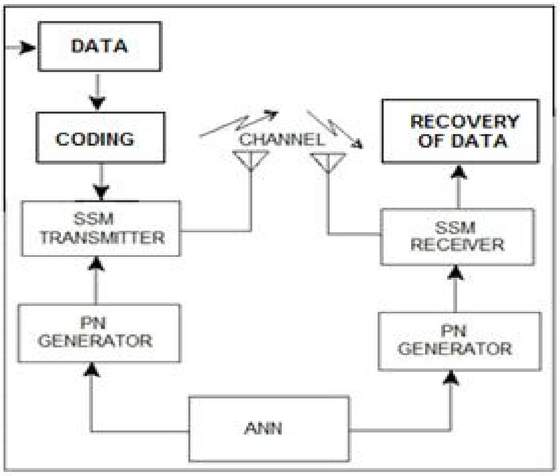

Figure 3 : System Model

$$O_x = \sum_{i=1}^{N} \beta_i \, g(w_i x + b_i) \quad (1)$$

where β_i is the bias value and w_i weight value between the i^{th} hidden neuron. The process of adjusting the weights and biases of the MLP is known as training. Training the MLP is done in two broad passes - one a forward pass and the other a backward calculation with error determination and connecting weight updating in between. The output from the hidden layer is obtained depending upon the choice of the activation function. The values of the hidden nodes are :

$$net_{mj}^{h} = \sum_{i=1}^{L} w_{ji}^{h} p^{mi} + \phi_j^{h} \quad (2)$$

The values of the of output node can be obtained as :

$$o_{mk}^{o} = f_k^{o}\left(net_{mj}^{h}\right) \quad (3)$$

Forward Computation: The errors can be computed as :

$$e_{jn} = d_{jn} - o_{jn} \quad (4)$$

The mean square error (MSE) is calculated as :

$$MSE = \frac{\sum_{j=1}^{M} \sum_{n=1}^{L} e^{2}_{jn}}{2M} \quad (5)$$

Error terms for the output layer are :

$$\delta^{o}_{mk} = O^{o}_{mk}\,(1 - O^{o}_{mk})\,e_{mn} \quad (6)$$

Error terms for the hidden layer :

$$\delta^{o}_{mk} = O^{o}_{mk}\,(1 - O^{o}_{mk}) \sum \delta^{o}_{mj}\, w^{o}_{jk} \quad (7)$$

Weight Update : Between the output and hidden layers

$$w^{o}_{kj}(t+1) = w^{o}_{kj}(t) + \eta \delta^{o}_{mk}\, o_{mj} \quad (8)$$

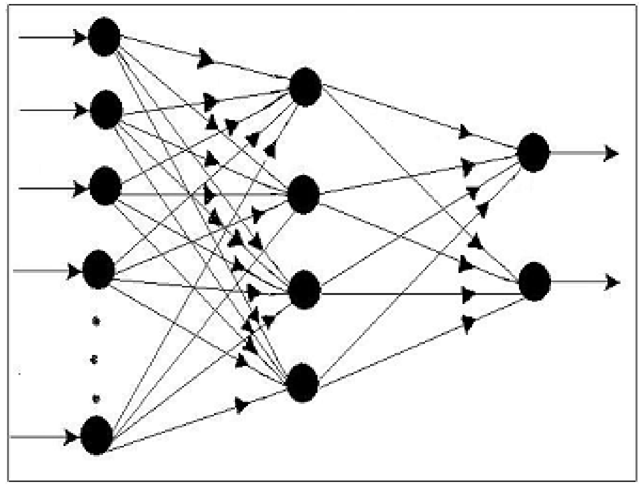

Figure 4 : Multi-layer Perceptron

Table I : Network Parameters

Sl. No.	Network Parameters	
	Item	*Description*
1	Network type	MLP
2	Hidden layers	2
3	Hidden layer size	10
4	Transfer function	Tangential sigmoidal
5	Performance function	LMSE
6	Training algorithm	Back Propagation

where η is the learning rate. One cycle through the complete training set forms one epochs. The above is repeated till MSE meets the performance criteria.This cycle constitutes the learning phase of the MLP [8].

B. Training and Testing

ANNs can generalize and correctly classify inputs unknown to them previously. A training set is used to help the ANN learn which is reflected by a continuous update of network weights and biases, and after training, each network go through a testing procedure to gather data for evaluation of its usefulness. One set of data is created for training the ANN. The data set consists of DPSK modulated signals along with ANN-assisted PN sequence. The DPSK modulated signal has a signal-to-noise (SNR) variation between -10 to 30 dB which makes 41 sets with signal variations. Further there are variations like Gaussian and fading (Rayleigh and Rician) channels. This way a total of 123 signalling conditions are obtained. Of each signalling condition atleast 10 sets are taken as samples to make the training robust. Similarly a testing set is created to validate the training. This set of data consists of data bits whose length is equal to the PN sequence and is presented to each ANN. Network specific

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TABLE II : PARAMETERS OF THE PN SEQUENCE FOR THE DSSSM SYSTEM

Sl. No.	Parameters of the PN Sequence for the DSSSM system	
	Item	*Description*
1	Chip rate (r_c)	8 KHz
2	Chip time (T_c)	0.0125 µs
3	Sequence length (N)	31 bits
4	Code length (NT_c)	0.3875 µs

procedures are then used to compare the output of each ANN against the desired outputs. The training time is a parameter that is independent of the test data and is the number of seconds spent training a particular network.

C. Evaluation

Running an ANN simulation produces a matrix of actual network outputs. These values can be compared to a target matrix of desired ANN outputs to evaluate the performance of each network. The input layer consists of a few number of nodes equal to the length of the PN sequence. The output layer has a size equal to the number of bits to be included in the ANN generated PN sequence. The performance function is the least mean of squared error (LMSE) which minimizes the average of the squared network errors. Once all the inputs have been presented, the training algorithm modifies the weights according to its procedure. The total number of epochs for each ANN is around 5000. The training of the ANN is carried out using four different training methods. These are

- Backpropagation with gradient descent (BPGD).
- Backpropagation with gradient descent and momentum (BPGDM).
- Backpropagation with gradient descent and adaptive learning rate (BPGDA).
- Backpropagation with gradient descent, momentum and adaptive learning rate (BPGDX).

Out of these four training methods, BPGD turns out to be most efficient in terms of training time, accuracy and number of epochs required to reach the desired goal.

D. Hamming and CRC coding

Hamming code is a linear error-correcting code which can detect up to two simultaneous bit errors, and correct single-bit errors. Thus reliable communication is possible when the Hamming distance between the transmitted and received bit patterns is less than or equal to one. By contrast, the simple parity code cannot correct errors, and can only detect an odd number of errors [9]. A cyclic redundancy check (CRC) is an error-detecting code designed to detect accidental changes to raw data, based on the theory of cyclic error-correcting codes. CRCs are so called because the check (data verification) code is a redundancy (it adds zero information to the message) and the algorithm is based on cyclic codes [9].

TABLE III : PARAMETERS OF THE PN SEQUENCE FOR THE FHSSM SYSTEM

Sl. No.	Parameters of the PN Sequence for the FHSSM system	
	Item	*Description*
1	Chip rate (r_c)	250 Hz
2	Chip time (T_c)	0.0040 µs
3	Sequence length (N)	31 bits
4	Code length (NT_c)	0.124 µs

E. System design

With reference to Fig. 3 the PN sequence used in the analysis of the DSSSM system has the parameters as shown in Table II. In both DS and FH systems a 32 bit binary stream is taken as the message signal. The data in this signal can take two amplitudes, where one amplitude corresponds to logical 1 and the other amplitude to logical 0. This data stream is multiplied with a cosine function of a higher frequency. In fact, this modulation can be considered as the primary modulation. Mathematically,

$$s(t) = 1 \text{ or } s(t) = -1 \quad (9)$$

such that the pre-modulated signal m(t) is given as

$$m(t) = s(t)\cos(2\pi f t) \quad (10)$$

where $f = f_1$ and $f = f_2$ are the two frequencies for s(t) = 1 and s(t) = -1 respectively taken such that these frequencies lie within the spread spectrum bandwidth.

For simplicity, it has been assumed that all amplitudes are equal to one. After the primary modulation, the signal is modulated again, to spread its frequency spectrum. This modulation is the multiplication of the signal m(t) with a digital signal of larger frequency range. The transmitted spread spectrum signal is given by

$$x(t) = m(t)\,c(t) \quad (11)$$

where c(t) is the PN sequence.

At the transmitter, binary symbols are transmitted with energy E per symbol. The noise n(t) added to this transmitted signal has an effect only on the amplitude. It depends on the signal-to-noise ratio (SNR). Hence the signal transmitted through the channel can be represented by the following equation

$$y(t) = x(t) + n(t) \quad (12)$$

To recreate data at the receiver, the signal is despreaded first and then normally demodulated. The despreading can only be successful if the code sequence generated in the receiver is exactly synchronised with that of the received signal. The parameters of the PN sequence used for the analysis of the FHSSM system are given in Table III. With each of the signal sets considered, a unique PN sequence is generated by the ANN. There is a one-to-one correspondence between the signal to be transmitted and the PN sequence generated. This correspondence is used at the receiver for recovery of the data. The ANN for a given input of received signal provides the unique PN code. The precision of the PN code can be varied with better ANN configuration and training.

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TABLE IV : BER FOR DIFFERENT VALUES OF THE JAMMING FACTOR OF DSSSM SYSTEM

Sl. No.	BER for different values of the jamming factor of DSSSM system		
	Jamming factor	*BER (without ANN)*	*BER (with ANN)*
1	0.1	0.0366	0.0307
2	0.4	0.0316	0.0271
3	0.5	0.0299	0.0237
5	0.7	0.0280	0.0225
6	0.8	0.0266	0.0202
7	1.0	0.0216	0.0186

TABLE V : BER FOR DIFFERENT HOPS OF THE PN SEQUENCE OF FHSSM SYSTEM

Sl. No.	BER for different hops of the PN sequence of FHSSM system		
	Number of hops	*BER (without ANN)*	*BER (with ANN)*
1	2 hops/symbol	0.0295	0.0286
2	10 hops/symbol	0.0250	0.0249

TABLE VI : BER FOR DIFFERENT VALUES OF THE JAMMING FACTOR OF FHSSM SYSTEM AT 2 HOPS/SYMBOL

Sl. No.	BER for different values of the jamming factor of FHSSM system at 2hops/symbol		
	Jamming factor	*BER (without ANN)*	*BER (with ANN)*
1	0.1	0.0295	0.0286
2	0.5	0.0288	0.0251
3	0.6	0.0274	0.0248
4	0.8	0.0255	0.0240
5	1.0	0.0233	0.0223

The entire system is trained and tested in a setup closely related to an environment where the SSM operates. The performance of the spread spectrum system in presence of partial band noise jammer is analysed for different fractions of the spread spectrum bandwidth. A jammer is considered that transmits noise over a fraction of the total spread spectrum bandwidth. The jammer signal is a Gaussian noise with a flat power spectral density over the jammed bandwidth. The jammer spreads noise of the total power J over some frequency range of bandwidth W_j, which is a subset of the total spread spectrum bandwidth W_{ss}. It is assumed that the shifts in the jammed band coincide with carrier hop transitions. It is experimentally found that when the fraction of the jamming bandwidth is decreased, the probability of the system being jammed is decreased but the jammed signals suffer a higher error rate, resulting in a degradation in the performance of the system and vice-versa. The error rate is also calculated by varying the number of hops per data symbol.

TABLE VII : BER FOR DIFFERENT VALUES OF THE JAMMING FACTOR OF DSSSM SYSTEM SYMBOLFOR HAMMING AND CRC CODE INFORMATION SEQUENCE

BER for different values of the jamming factor of DSSSM system				
Jamming factor	BER (without ANN for Hamming)	BER (with ANN for Hamming)	BER (without ANN for CRC)	BER (with ANN for CRC)
0.1	0.0265	0.0240	0.0299	$1x10^{-4}$
0.4	0.0249	0.0234	0.0249	$1x10^{-4}$
0.5	0.0218	0.0207	0.0233	$1x10^{-4}$
0.7	0.0187	0.0181	0.0216	$1x10^{-4}$
0.8	0.0187	0.0181	0.0183	$1x10^{-4}$
1.0	0.0169	0.0156	0.0183	$1x10^{-4}$

TABLE VIII : BER FOR DIFFERENT HOPS OF THE PN SEQUENCE OF FHSSM SYSTEM SYMBOLFOR HAMMING AND CRC CODE INFORMATION SEQUENCE

BER for different hops of the PN sequence of FHSSM system				
Number of hops	BER (without ANN for Hamming)	BER (with ANN for Hamming)	BER (without ANN for CRC)	BER (with ANN for CRC)
2 hops/symbol	0.0251	0.0242	0.0251	0.0242
10 hops/symbol	0.0246	0.0240	0.0246	0.0240

III. RESULTS AND DISCUSSION

Based on the data generated by simulation of DSSSM and FHSSM systems, relationship using DPSK modulation technique between BER as a function of the jamming factor and number of hops is obtained using the PN sequence Tables IV – VI. Table IV shows that with the increase in the jamming factor from 0.1 to 1.0, the BER decreases from 0.0366 to 0.0216 for the PN sequence generated using shift registers while the BER decreases from 0.0307 to 0.0186 for the PN sequence generated using ANNs. Table V shows that in case of the FHSSM system using the PN sequence generated using shift registers, as the number of hops is increased from 2 hops/symbol to 10 hops/symbol, the BER is 0.0295 and 0.0250 respectively and 0.0286 and 0.0249 respectively for the PN sequence generated using ANNs. Table VI shows that in case of the FHSSM system, keeping the hop rate at 2 hops/symbol, as the jamming factor is increased from 0.1 to 1.0, BER of 0.0295 and 0.0233 respectively is generated using the PN sequence generated using shift registers while the BER is 0.0286 and 0.0223 in case of the PN sequence generated using ANNs. Based on the data generated by simulation of the DSSSM and FHSSM systems, relationship using DPSK modulation technique between BER as a function of the jamming factor and number of hops is obtained in Tables VII–IX for both Hamming and CRC coded information

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sequence. Table VII shows that with the increase in the jamming factor from 0.1 to 1.0, the BER goes down from 0.0265 to 0.0169 for the PN sequence generated using shift registers. The corresponding BER is 0.0240 at jamming factor 0.1 and 0.0156 at jamming factor of 1for the PN sequence generated using ANNs for the Hamming coded sequence. The BER is 0.0299 at jamming factor 0.1 and 0.0183 at jamming factor of 1 for the PN sequence generated using shift registers. For the CRC coded sequence the BER is $1x10^{-4}$ at jamming factor 0.1 and $1x10^{-4}$ at jamming factor of 1 for the PN sequence generated using ANNs. Table VIII shows that in case of the FHSSM system using the PN sequence generated using shift registers, as the number of hops is increased from 2 hops/symbol to 10 hops/symbol, the BER is 0.0251 and 0.0246 respectively and 0.0242 and 0.0240 respectively for the PN sequence generated using ANNs for both the Hamming coded sequence and the CRC coded sequence. Table IX shows that in case of the FHSSM system, keeping the hop rate at 2 hops/symbol, as the jamming factor is increased from 0.1 to 1.0, BER of 0.0265 and 0.0169 respectively is generated using the PN sequence generated using shift registers while the BER is 0.0240 and 0.0156 in case of the PN sequence generated using ANNs for the Hamming coded sequence while the BER is 0.0299 and 0.0183 for the PN sequence generated using shift registers and $1x10^{-4}$ in case of the PN sequence generated using ANNs for the CRC coded sequence. From the above tables it is seen that when the information sequence is coded using Hamming and CRC coding the BER has reduced though the use of coding bits leads to some waste in bandwidth. The BER with CRC coding has fallen to $4x10^{-4}$ and 10^{-4} in Rayleigh fading channels without ANN and Rayleigh fading channel with ANN respectively over the SNR range -10dB to 30 dB. It represents 13% and 14% improvement compared to uncoded forms. Thus the use of ANN-assisted PN sequence generation and coding is justified for application in DS/FH SSM in wireless channels.

IV. Conclusion

The work shows the effectiveness of the use of ANN for PN sequence generator and coding for both DS and FH SSM systems. The extracted results show that the ANN assisted PN sequence generator helps in providing superior BER values in both Gaussian and Multipath faded channels. The work also demonstrates that performance improves further with the use of coding. The combination proves to be effective in wireless channels. The ANN assisted PN sequence is robust enough to prevent false triggering which also helps it to provide better performance in wireless channels. Thus, the system proposed can prove to be effective and enhance performance of DS/FH SSM transmission.

Table IX : Ber For Different Values Of The Jamming Factor Of Fhssm System At 2 hops/symbolFor Hamming And CRC Code Information Sequence

BER for different values of the jamming factor of DSSSM system				
Jamming factor	BER (without ANN for Hamming)	BER (with ANN for Hamming)	BER (without ANN for CRC)	BER (with ANN for CRC)
0.1	0.0265	0.0240	0.0299	$1x10^{-4}$
0.4	0.0249	0.0234	0.0249	$1x10^{-4}$
0.5	0.0218	0.0207	0.0233	$1x10^{-4}$
0.6	0.0218	0.0196	0.0230	$1x10^{-4}$
0.7	0.0187	0.0181	0.0216	$1x10^{-4}$
1.0	0.0169	0.0156	0.0183	$1x10^{-4}$

References

[1] G. Ponuratinam, B. Patel and S. S. R. K. M. Elleithy, “Improvement in the Spread Spectrum System in DSSS, FHSS, and CDMA,” Computer Science and Engineering Department, University of Bridgeport, Bridgeport, CT 06605.
[2] M. L. Wu, K. A. Wen and C. W. Huang, “Efficient Pseudonoise Code Design for Spread Spectrum Wireless Communication Systems”. IEEE Transactions on Circuits and systems II: Analog and Digital Signal Processing, Vol. 48, No. 6, June 2001.
[3] S. Haykin, “Digital Communications,” John Wiley and Sons Inc, United Kingdom, 2010.
[4] S. Zoican,”Frequency Hopping Spread Spectrum Technique for Wireless Communication Systems,” IEEE Transactions on Communications, 1998.
[5] T. S. D. Tsui and T. G. Clarkson, “Spread Spectrum Communication Techniques,” Electronics and Communication Engineering Journal, pp 3-6, February 1994.
[6] G. J. R. Povey and P. M. Grant, “Simplified matched filter receiver designs for spread spectrum communications applications,” Electronics and Communication Engineering journal, April 1993.
[7] P. de Bruyne, 0. Kjelsen and 0. Sacroug, “Spread Spectrum Digital Signal Synchronization using Neural Networks,” IEEE Transactions on Communications, 1992.
[8] S. Haykin: Neural Networks: A Comprehensive Foundation (2nd Edition), Pearson Education, New Delhi, 1998.
[9] W. E. Ryan and S. Lin, Channel Codes: Classical and Modern, Cambridge University Press, New York, 2009.

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